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Abstract

This paper studies the effect of the diesel price on trade flows across space within the United States. Using a structural gravity model with spatially autocorrelated flows applied to the inter-state trade, we find that an increase in diesel price reduces the volume of trade and that this effect increases with the distance between trade partners. Furthermore, such price shock increases trade within a state and with nearby partners. Finally, the social welfare effects of a 10% increase in diesel price vary by states, with the median corresponding to a 0.69% loss in the real GDP or $82 billion nationwide.

Keywords: trade, distance, oil price, gravity model

JEL classifications: O24, Q49, R13

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1. Introduction

The last 15 years has seen a dramatic rise in oil prices, tracked by the Energy Information Administration (EIA), to a record high of $147 a barrel, as well as prices falling off a cliff to $30/barrel. The implications of these oil price shocks on the economy are still being explored but such fluctuations are bound to have an effect on trade dynamics. Expectedly, higher oil prices should act as a stronger friction reducing trade, distorting the directionality of its flows, and affecting social welfare. Yet, the degree of change and its distributional attributes are obscure and need to be investigated. The purpose of this paper is to explore the oil price-trade relationship across distance and to shed light on the distributional effects and welfare effects of oil price shocks on the U.S. interstate trade system.

Trade flows between two geographic areas are not only determined by relative endowments but also by a set of costs that act as a friction to trade. This can be conceptually understood from Samuelson's iceberg transportation cost model (1954). Oil prices enter into the transportation cost through derived fuel products such as diesel. Conventional trade theory would lead us to expect that price changes would offset each other; as Anderson (2011) notes, a uniform percentage change in trade costs across all partners will yield no change in volume of trade. In such a case, empirical modeling would reduce oil price effects to a simple multiplier. However, as a transportation-based trade cost, fuel price relates closely to the role of distance. Distance is commonly used as a proxy for transportation costs, yet the linear form does not model freight costs well (Head and Mayer, 2014, pg 189). Furthermore, while distance adds the spatial component to trade models, it does not allow for heterogeneous effects that arise from the factors it proxies. For instance, Cheong et al. (2016) empirically find different distance effects on intensive and extensive margins in trade. Scholars have introduced multiple ways to incorporate the heterogeneity. Lankhuizen et al. (2015) use multiple dimensions of distance to classify traded commodities into distinct homogenous groups, and Bertho et al. (2016) separate distance frictions from maritime transport costs.

Motivated by these insights on the heterogeneity of the fuel price effects over distance, we establish a trade model that explicitly accounts for the interaction between fuel price and distance. Moreover, our general equilibrium framework incorporates the feedback effects and multilateral effects, allowing common changes to have differential effects across geography, as found in Behrens et al. (2006) and Allen and Arkolakis (2014). Given the spatial interdependent nature of the trade flow, we also consider a spatial econometric variant of structural gravity models that allows for spatial heterogeneity of shocks through feedback and multilateral effects. Our work is built upon Behrens et al. (2012), which presents a general equilibrium model interacting all flows with common origin based on the size of the destination. Using a similar approach, Anderson and Yotov (2016) show heterogeneous effects of large free trade agreements in terms of welfare changes.

In this paper, we apply a structural gravity model of trade to the U.S. inter-state trade across the years of 2002, 2007, and 2012. Oil price effects are introduced in the form of regionally varying diesel fuel prices. Our findings confirm that bilateral trade flow is significantly dampened by higher diesel prices, more so when the distance between trading partners is larger. We also consider a spatial econometric model to directly incorporate spatial interdependence of trade flows, and we find consistent effects. Then we consider a 10% nationwide price shock in a general equilibrium framework, where states are allowed to adjust output, expenditures, and resistance to trade across all partners. Overall we find that trade within the U.S. becomes systematically more local as oil becomes more expensive. This is exemplified in the case where trade from Massachusetts to California falls by 2.9% but only by 0.47% to New York, a 2.43 percentage point difference. Furthermore, trade within the borders of Massachusetts actually increases by 0.53%. While trade is partially redistributed across the space, the net effects yield a median 0.69% welfare loss in terms of real GDP, and $82 billion for the nation as a whole.

We contribute to the trade literature by showing that even within the U.S., where distance faced is much smaller than internationally, trade flows are still responsive to oil prices. Such high sensitivity of trade to a single and volatile natural resource highlights the importance of technological change in energy and transportation. For instance, regulations on fuel economy such as requirements to deploy vehicle upgrades and systematic revamping of transportation fleets towards electric could potentially alleviate the reliance on oil. The negative impact on trade and welfare should also be considered in the cost-benefit analysis when designing national oil tax policy and state fuel policy. In particular, we demonstrate the mechanism in which a uniform shock creates non-zero effects in general equilibrium, which is contrary to trade theory and suggests that the functional form of trade costs is important. Our findings highlight the heterogeneity of the negative effects of fuel price over space, which are necessary to consider when designing spatially blind policy such as a national oil tax. Finally, we show the regional connectivity in the U.S. states by incorporating the regional border effects as a non-conventional trade cost in the gravity model of intranational trade.

2. Literature

Trade costs, the obvious channel for oil price to influence trade, are a main factor of interest in trade analysis. Trade costs, as described by Anderson and van Wincoop (2004), are broadly defined, including both policy barriers and transportation costs. The authors show that trade costs remain large and exist in both cross-border and within-border trade. Due to the unreliability of transportation cost estimates, distance is virtually always used in trade models as a proxy for trade costs (Head and Mayer, 2014; Anderson and Yotov, 2010). Despite of technological advances, distance remains a significant cost and continues to shape trade even for developed nations (Boulhol and de Serres, 2010). While distance has worked well so far, Head and Mayer (2014) discuss the need to reevaluate the functional form of transportation costs. Several studies have attempted to refine transportation costs. For instance, Combes and Lafourcade (2005) incorporate factors such as infrastructure and energy into cost measures within France. Hummels (2007) unpacks transportation costs and finds that fuel costs are central to determining freight costs, citing several oil price shocks. Hummels et al. (2009) investigate the effects of high shipping costs on trade by exploring market power induced transportation costs markups and its subsequent negative effect on trade with developing countries. Most strikingly, eliminating price markups would increase trade from the U.S. to Latin America by 5.9%.

Other studies directly relate oil prices to trade. For instance, Brun et al. (2005) finds that including oil price as a trade cost resolves the conundrum that the elasticity of trade with respect to distance increases over time. This highlights the importance of incorporating oil price in a trade model. The work of Vezina and von Below (2013) explores the effect of oil price on international trade using a formal structural gravity model with data starting in 1962. They find significant negative coefficients for both the distance and the interaction between oil price and distance. In the international trade context they conclude that higher oil prices make trade less global but they do not explore the spatial dependence or the distributional effects in general equilibrium. Similarly, when examining the trade boosting effects of the euro currency union, Nanovsky (2015) finds a negative oil price distance interaction term within a formal gravity model of international trade over the years 1952-2012. However, neither Vezina and von Below (2013) nor Nanovsky (2015) investigate the heterogeneous impact on trade that results from the nonlinear impact of oil price changes over distance.

While there is evidence of an oil price trade relationship in international trade, the sub-national setting has not yet been considered. There are of course no tariffs or quotas imposed on trade within the United States, and common international barriers such as different languages and currencies are not applicable. Despite the illusion of openness of trade within a nation, certain biases may act just as trade costs when considering intra-national trade such as agglomeration, home market bias, or structural economic links. It is important to not only consider within-state trade but also differentiate interstate trade with different types of partners.

Trade patterns are well known to concentrate within borders to a large degree, so much so that the phenomenon is referred to as a "border effect" or "home bias" (see, among others, McCallum, 1995; Anderson and van Wincoop, 2003; Evans, 2003; Egger and Larch, 2012). In the international setting the diverting effect of crossing a national border has been traditionally modeled as a trade cost. Within a country, for example the U.S. states, borders are not apparent deterrents to trade. Yet, many studies have shown that sub-national borders negatively affect trade flows. Starting with Wolf's (2000) paper investigating the U.S. interstate trade flows in 1993, "home bias" is introduced in a gravity model as a dummy variable indicating within-state trade. The results show that the state border effect is significant and rather large. Coughlin and Novy (2011) even claim that trade is so locally clustered that state border effects are larger than international border effects. Millimet and Osang (2007) revisit the home bias effect and find it to be smaller but still significant. Craft and Klein (2015) confirm that the home bias of the U.S. domestic trade is persistent and remains large in 2007 as compared to 1949. Based on 2007 data also, Yilmazkuday (2012) further confirms the home bias across states and varieties of goods. Moving outside the U.S., Kashiha et al. (2016) find nontrivial border effects in the wine market of Europe, a free trade zone. Anderson and Yotov (2010) and later Agnosteva et al. (2015) find province specific home bias for Canadian inter-provincial trade flows. In a general equilibrium, they find strong home bias across all provinces, with heterogeneity dependent on geographic size and remoteness.

Subnational trade patterns can be in part explained by industry structure and links, tied to firm location and agglomeration. Besides locating near and trading with large home markets demanding final goods i.e., the "home market effect" (Krugman, 1980), firms are sensitive to transportation costs for intermediate goods as well, resulting in agglomeration (Krugman and Venables, 1995; Venables, 1996; Alonso-Villar, 2005). Yilmazkuday (2010) empirically finds that intermediate inputs lead to systematic connections between agglomeration and trade. While agglomeration implies the local nature of trade, the structural links are not limited to explaining within state trade but also structurally related regions. For instance, the Chicago region experienced a "hollowing out" phenomenon in the last 30 years, i.e. a decrease in density of intermediate goods traded in the local economy (Hewings et al, 1998); yet meanwhile, large trade occurred among the Midwest through intra-industry trade along a production chain (Munroe and Hewings, 1999). Parr et al. (2002) propose moving past a divide of spatially constrained and unconstrained economic activity, i.e., the agglomeration effects, to include partially constrained, multi-state areas such as the Midwest. In an extensive analysis of the historical trade patterns among the U.S. states, Lee (2010) finds a set of “trading zones,” or tight geographic pattern, emerges based on similarity of trade inflows and outflows. These areas turn out to be largely aligned with the eight “regions” of states defined by the BEA on the basis of economic similarity. This motivates our use of the BEA regions as part of the border effects in our trade model.

While border effects seem to imply bilateral trade happens more intensively in blocs of states, it is important to note that trade flows are spatially dependent on each other. Spatial interdependence of flows arises because any geographic area used is repeated throughout several observations and any change in one observation is likely to affect all other related ones. LeSage and Pace (2008) point this out and discuss the spatial dependences based on common origin, common destination, and even origin-destination dependence. Behrens et al. (2012) note the necessity to account for multilateral effects, i.e., effects across all trading partners, in the theoretical structural gravity model famously used by Anderson and van Wincoop (2003). They propose a spatial model to account for the multilateral effects, and they suggest an interaction weight matrix based on population share and then a spatial lag of the dependent variable to interlink trade flows with common destination. Using their model, they find that the estimated U.S.-Canada border effect is smaller than previously estimated.

3. Methodology

3.1 Theory

This paper analyzes the oil price and distance relationship using a gravity model, which is commonly used to describe trade flows between a given origin destination pair. The structural gravity model we used can be defined as the following (Anderson, 1979, 2011; Anderson and van Wincoop, 2003; Anderson and Yotov, 2010):

$$X_{ij} = \frac{Y_i Y_j}{Y^w} \left(\frac{t_{ij}}{\Pi_i \mathrm{P}_j} \right)^{1-\sigma} \tag{1}$$

$$(\Pi_i)^{1-\sigma} = \sum_j \left(\frac{t_{ij}}{\mathrm{P}_j} \right)^{1-\sigma} \frac{Y_j}{Y^w} \tag{2}$$

$$(\mathrm{P}_j)^{1-\sigma} = \sum_i \left(\frac{t_{ij}}{\Pi_\mathrm{i}} \right)^{1-\sigma} \frac{Y_i}{Y^w} \tag{3}$$

Where X_{ij} is the trade flow between origin (exporter) *i* and destination (importer) *j*, Y_i is total output or the size of origin economy *i*, Y_j is the total expenditure or size of destination economy *j*. Furthermore, t_{ij} is a set of vectors representing bilateral trade costs between the origin-destination pair, and has traditionally contained a coefficient of interest with which to aid policymaking or perform counterfactual exercises. Trade costs can be defined in several ways as long as the multiplicative form in (1) holds. Π_i and P_j are “multilateral resistance” terms, specifically outward multilateral resistance and inward multilateral resistance respectively. The outward multilateral resistance can be interpreted as seller's incidence, while the inward multilateral resistance can be interpreted as buyer’s incidence and is equivalent to a markup for a bundle of goods importer *j* would pay in the system market (Anderson and Yotov, 2010). The structural gravity form utilizes constant elasticity of substitution (CES) preferences and products variety is different by origin, as in Armington (1969). As Anderson and Yotov (2010) note, using a framework outside of the Armington assumption is possible but currently has some unexplored implications. The CES structure will allow the incorporation of trade flows in a process of general equilibrium calculation as represented in Section 6.

3.2 Empirical Application

In order to describe the effect of an oil price shock on trade flows between a given origin i and destination j, consider the structural gravity model in (1). Spanning three time periods, namely the years 2002, 2007, and 2012, the model will include time index t for every term, although we omit the notation below for simplicity. Next, t_{ij}, the bilateral trade costs, are composed of variables often used in the literature, as well as of our variable of interest.

$$\left(t_{ij}\right)^{1-\sigma} = e^{\beta_1 lnDIST_{ij}+\beta_2(lnDIST_{ij}x lnDIESEL_{ij})+\beta_3 NEIGHBOR_{ij}+\beta_4 HOME_{ij}+\beta_5 REGION_{ij}} \quad (4)$$

Log distance between each i and j is *lnDIST,* which does not change over time. The variable of interest is the coefficient for the interaction between *lnDIST* and *lnDIESEL.* Rather than using the price of a barrel of oil without any spatial heterogeneity, we use the regional diesel prices to proxy the price of oil. Taking the average of the prices of location i and j will result in a unique price index for each origin destination pair in time period t. Interacting this price index with *lnDIST* adds non-linearity. That is, a change in fuel price *lnDIESEL* will increase the trade cost term *lnDIST*×*lnDIESEL* more as the distance increases.

Next is a set of three dummy variables to proxy the "border" type of trade costs and capture the underlying spatially economic interaction. The *NEIGHBOR* variable takes value of 1 when i and j are contiguous to each other, and 0 elsewhere. *HOME* takes the value of 1 when $i = j$ meaning that the trade flow is *intra*state, and 0 elsewhere. This variable captures the effect of a home bias or a state border effect. Both *NEIGHBOR* and *HOME* have been shown to significantly affect trade (Head and Mayer, 2014). *REGION,* takes the value of 1 when i and j are in the same economic region, and 0 otherwise. Much like the *HOME* variable, the *REGION* variable captures the trade bias a state experiences with its regional "partners" due to structural similarity. These dummy variables for the border trade costs are exogenous based on location, allowing a simple way to control for fundamental tendencies of sub-national trade.

Next, substitute trade costs (4) into the baseline gravity equation (1).

$$X_{ij,t} = exp[\beta_0 + \beta_1 lnDIST_{ij} + \beta_2(lnDIST_{ij} x lnDIESEL_{ij,t}) + \beta_3 NEIGHBOR_{ij} + \beta_4 HOME_{ij} + \beta_5 REGION_{ij} + \beta_6 lnY_{i,t} + \beta_7 lnY_{j,t} + \eta_{i,t} + \theta_{j,t}] + \epsilon_{ij,t} \quad \forall i,j,t \quad \epsilon \sim (0, \sigma_\epsilon^2) \tag{5}$$

The parameters η and θ represent origin-time and destination-time fixed effects respectively and they control for the unobserved (log of) multilateral resistance terms. A critical factor in model specification is the inclusion of these directional fixed effects (both importer and exporter specific) to control for multilateral resistance instead of a proxy such as a remoteness index, as proposed by Anderson and van Wincoop (2003) and emphasized by Feenstra (2004). The baseline econometric model (5) is estimated using a Poisson Pseudo Maximum Likelihood Estimator with Ericker-White robust standard errors, suggested by Silva and Tenreyro (2006, 2011), has become the standard for gravity model estimation. This estimator corrects the heteroskedasticity inherent in trade data, which may actually bias the estimates, and it also allows for the utilization of zero-value trade flows that contain useful information. To correct for serial correlation within each trade pair, state-pair clustering of standard errors is also applied. Each model specification will be tested across the baseline as well as samples with differing treatment of zero trade flows, as discussed in the data section.

As a recent paper by Fally (2015) shows, the PPML estimation method with directional fixed effects fully satisfies the theoretical constraints of multilateral resistance, so we can confidently proceed with modeling the levels of trade as a function of fixed effects to satisfy the theory. This also holds when the Y variables are omitted, and the activity variables are absorbed into fixed effects. We can expect the coefficient β_1 to be negative, as suggested by theory and consistent with gravity trade literature. Our variable of interest β_2 is expected to be negative, which would imply that as the price of diesel increases, trade will decreases, and even more so for longer distances. The coefficients on *NEIGHBOR, HOME, and REGION* are all expected to be positive, indicating larger trade flows between neighbors and within state and region respectively. *HOME* is expected to have the largest magnitude. Finally, when used, Y or size/activity of origin and destination, will be positive.

4. Data and Preliminary Analysis

The primary source of data utilized in this study is the Commodity Flow Survey (CFS) published by the Bureau of Transportation Statistics. It covers the years 2002, 2007, and 2012. The CFS spans 41 commodities classified at the two-digit SCTG level and published data are available at different dimensions and aggregation levels. Specifically, we use total commodity flows between origin and destination for the 50 U.S. States and the District of Columbia. Trade flows are reported by total value of shipment in current year $ millions. As with all trade data, there is the issue of censored trade flows or missing values. For robustness checks, we define three samples: one baseline in which all non-zero trade flows are included, a robustness sample that omits the censored trade flows, and a second robustness sample that includes all possible observations treating both censored and missing trade as zeros.

Next, several variables are constructed to proxy trade costs. Distance is calculated as the arc distance between centroids of states using the Vincenty method (Vincenty, 1975). For the trade flows within a given state, the average shipment distance in miles as reported by the CFS is used, and further averaged over all time periods to avoid issues with geometric computation of within state distance noted by Head and Mayer (2002). The diesel fuel price data are from the Energy Information Administration (EIA), which contains the average annual price across 8 geographic areas defined by the EIA. In the case of the flow data, every observation will have two prices, one for the origin and one for the destination. The final price for a given flow is the average price between origin and destination and adjusted for inflation. As we see in Figure 1, showing the diesel price across regions in 2002, 2007 and 2012, the real diesel price ($2012) does not vary dramatically across space, but an increase is noticeable over time from a national average of $1.618 ($2012) in 2002 to an average of $3.968 ($2012) in 2012.

To represent the size of a state's economy, the annual state level gross domestic product reported by the Bureau of Economic Analysis (BEA) is used. The trade regions are defined as the 8 BEA-defined regions based on geography and homogeneity of economic characteristics such as industrial composition and demographics. The left panel of Table 1 displays the descriptive statistics for the sample where all aggregate flows are included while the right panel of Table 1 shows the sample in which the zero trade flows are dropped. All data are reported in current dollars, so we use the US Consumer Price Index to adjust the trade to 2012 dollars.

4.1. Border Effects of Trade

In Table 2, trade flows are shown between each region, as a proportion of all flows from a given region. The diagonal element shows the volume of trade flows that remains within the regional "borders," which clearly represents a very large share of total trade and demonstrates the importance of the regional linkages between economies. For example, 58% of the trade originating in the Great Lakes remains in the region. Furthermore, we can distinguish the trade that remains within state borders from the one that goes to regional or even national trading partners. Figure 2 is a bar chart of the composition of each states' outgoing trade flow (export) volumes, grouped together by their respective regions. About 40% of the trade flows remain within the state that they originate from, and 20-25% of the trade flows are between states in a common trade region. The shares show that a large amount of trade originated from any given state is destined for a small fraction of states. This is evidence for the underlying agglomeration economies within states, as well as multi-state network effects, all of which serve as motivation to incorporate regional "border" effects in addition to state border effects.

4.2. Spatial Autocorrelation

Next, we test the spatial interdependence of the U.S. intrastate trade, i.e. the autocorrelation of trade flows. Two different varieties of spatial weight matrix will be considered. The first uses a k nearest neighbor approach and is constructed for both the origin and destination, as presented by LeSage and Pace (2008). That is, with an origin-centric ordering of our data, a weighting matrix $\mathbf{W}_{\mathrm{o}} = \mathrm{I}_{\mathrm{n}} \otimes \mathrm{W}_{\mathrm{k4}}$ represents the $k = 4$ nearest neighbors around origin i, and a weighting matrix $\mathbf{W}_{\mathrm{d}} = \mathrm{W}_{\mathrm{k4}} \otimes \mathrm{I}_{\mathrm{n}}$ represents the $k = 4$ nearest neighbors around destination j. Both are row-standardized. This type of weight scheme results in 4 neighbors for every trade flow observation, all equally weighted. The second type of weight matrix used is an inverse distance matrix, and is also separate for the origin and destination. Let the matrix **D** be a symmetric (n×n) matrix with the inverse distance between every i and j, with the diagonal being the internal distance of each observation $i = j$. We can expand the weighting matrix to distinguish the trade flows based on the same origin or same destination. Let $\mathbf{M}_{\mathrm{o}} = \mathrm{I}_{\mathrm{n}} \otimes \mathbf{D}$ and $\mathbf{M}_{\mathrm{d}} = \mathbf{D} \otimes \mathrm{I}_{\mathrm{n}}$. In order to ensure that a particular origin-destination flow is not a "neighbor" of itself, the diagonal will be set to zeros in both matrices. The final weighting matrix $\mathbf{W}_{\mathrm{o}}$ is equal to $\mathbf{M}_{\mathrm{o}} - \mathrm{diag}(\mathbf{M}_{\mathrm{o}})$ and the weighting matrix $\mathbf{W}_{\mathrm{d}}$ equals $\mathbf{M}_{\mathrm{d}} - \mathrm{diag}(\mathbf{M}_{\mathrm{d}})$. These matrices will relate a particular origin-destination flow to those that share the same origin (or destination), weighted by the distance between the common origin (or common destination) and all other destination (or all other origins). Again, both weighting matrices are row-standardized and each observation has (n-1), or 50 neighbors. In addition the k-nearest neighbors and inverse distance matrix described earlier, we will also consider the interaction weight matrix proposed by Behrens et al. (2012), which is based on the national population share of each geographic area. The matrix is constructed as $\mathbf{W} = [\mathrm{S}\ \mathrm{diag}(\mathrm{L})] \otimes \mathrm{I}_{\mathrm{n}}$, where S is a n×n matrix of 1s and diag(L) is a n×n diagonal matrix of population shares for each area.

Table 3 reports the Moran's I statistic estimated for each of the three years in our sample. All of the estimates are significant and indicate a positive autocorrelation of trade flows with common origin or destination, suggesting destination and origin-based dependence respectively. Furthermore, the statistics for the destination-based weights are very similar to their respective origin counterparts. The k4 weight matrix is also capturing a much more local effect, and Moran's I is slightly larger in magnitude than with distance-based matrix which relates all States in the U.S. through trade flows sharing common point. These weight matrices seem appropriate for the data and will be applied later in the gravity model.

5. Results

5.1 Baseline

First, we describe our baseline results from estimating Equation (4), across three sub-samples. Column (1) in Table 4 corresponds to the baseline model where all zero trade flows are omitted (denoted as $X > 0$). Column (2) uses the same specification but omits the censored trade flows that are not reported as true zeros (denoted as $X \neq S$, where "S" is a CFS flag for censored data). Column (3) includes all possible observations and all missing trade is considered zero (denoted as $X \geq 0$). Columns (4) – (6) estimate the respective models in (1) – (3) but omit the control variables Y_i and Y_j, in which case their effects are absorbed by the state fixed effects. Across the columns, we notice no concerning differences among the estimation results in terms of coefficients or model fit. In particular, columns (3) and (6) are the most desirable models because they include a full Origin-Destination flow matrix, i.e., all possible observations of trade flows. Their coefficients do not differ at all, except for the intercepts and fixed effects terms.

Our variable of interest *lnDIST*×*lnDIESEL* is significant and negative, which indicates that, holding distance constant, an increase in diesel price decreases the trade flow *X*. Furthermore, the larger the distance, the same increase in diesel price will decrease trade flow *X* by a greater amount. Our coefficient of -0.608 on *lnDIST* is lower than usually estimated in gravity models (median of -0.89, mean of -0.93, according to Head and Mayer, 2014), however our interaction captures part of the distance effect. To make a comparison, we compute the elasticity using the coefficients for both *lnDIST*×*lnDIESEL* and *lnDIST* from column (3). The elasticity of trade with respect to distance at any given price of diesel is shown in the left panel of Figure 3, and the elasticity of trade with respect to the price of diesel at various distances is presented in the right panel of Figure 3. Interestingly, our elasticity with respect to distance is still lower than the average of -0.93 found in the literature. Figure 3 suggests that trade is relatively inelastic to distance and the magnitude only increases moderately over a range of diesel price, demonstrating that distance has slightly larger "friction" at higher diesel prices. On the contrary, the responsiveness of trade to diesel price is very elastic and increases sharply as distance increases. Simply put, trade between far away partners is more sensitive to diesel price fluctuations.

The estimates of the three other trade cost variables are all positive and of reasonable magnitudes in Table 4. First, *HOME*, is very consistent with structural gravity estimates from the literature (median of 1.55, see Head and Mayer, 2014). It indicates a bias for states to keep trade within their own borders. The coefficient of 1.54 can be translated into a ratio of 4.67 (exp(1.54)=4.67), implying that the within state trade is 4.67 times as such as the trade outside of a state. The *NEIGHBOR* coefficient is close to the contiguity coefficients in the literature using structural gravity (median 0.52, mean 0.66, see Head and Mayer, 2014), and suggests that states in fact have a tendency to trade more with contiguous states. The unique trade cost proxy to this model, *REGION,* is intended to capture the tendency of a state to trade with its regional partners. The coefficient is positive and significant, despite *NEIGHBOR* also being present. We find that states have a regional partner trading bias with a ratio of 1.36, everything else held equal. Our *REGION* dummy is comparative to the coefficients usually found in the literature for international regional trade agreement, which has a similar coefficient in the literature (mean 0.36, see Head and Mayer, 2014). The estimates of the three dummy variables show that despite free trade, the trade frictions are still present within the U.S.

5.2 Robustness to Transportation Mode

Our baseline model does not distinguish the transportation modes. In reality, the composition of transportation mode use can differ across trade flows, and modes may have different sensitivity to oil price depending on fuel efficiency. An example is trucking, which has poor fuel efficiency, only 3 miles/gallon of diesel. Such fuel intensiveness results in fuel comprising 46 percent of overall operating costs (DOT, 2008). Furthermore, 39% of the total average marginal costs of trucking operations are attributed to fuel (ATRI, 2014). On top of this, the U.S. is geographically large, spanning 3,000 miles from New York to California, and leads to major consumption of diesel fuel (30 billion gallons) and vehicle miles (184 billion) traveled by trucks (DOT, 2016). Hence, it is expected trade moved by truck is extra sensitive to price and any price effects relative to other transportation mode. In this section, we use a homogeneous subsample of trade moved by trucks to evaluate the price and distance effects. It is worthwhile to note that when the data are reported at the transportation mode level, the likelihood of censoring increases, and even more so for non-truck modes. Hence it is infeasible to estimate mode-specific price effects using all trade data.

In Table 5 we present the estimation results for the truck subsample where the same three sample treatments are applied as in Table 4: all non-zero flows (column 1), all non-zero flows and true zero flows (column 2), and all flows (column 3). The non-zero flow sample is about 10% smaller than that of the baseline sample. The estimation results show that all three subsamples have significant coefficients, with unchanged signs and similar magnitudes. The truck subsample yields larger point estimates of lnRDiesel×lnDist coefficient and lnDist coefficient (column 3 in Table 5) as compared to these in the baseline (column 6 in Table 4). We test the null hypotheses that the coefficients are equal in the two models. The Chi-statistic has a p-value of 0.1076 for the lnRDiesel×lnDist coefficient, and a p-value of 0.0000 for the lnDist coefficient. This suggests that trade by truck displays a greater sensitivity to distance but the interaction effects of the diesel price and distance is similar to that in the baseline case. This is likely because the majority of the trade in the baseline sample was moved by truck. It is reported that 73% of all trade value is moved by truck (DOT, 2012 table 1b). Hence we conclude from the robustness test that the heterogeneous transportation mode composition in the baseline sample only has limited effects on the estimates.

5.3 Spatial Robustness

In this section, we directly incorporate the spatial interdependence of flows through a model including the spatial lag of the regressor, or SLX model (Vega and Elhorst, 2015). While there have been many spatial econometric advances in modeling flows, there have been limited applications to the trade flows. Le Sage and Pace (2008) and LeSage and Satici (2013) discuss the use of spatially lagged origin and destination characteristics to represent the market potential of the origin's and destination's surrounding areas and introduce interdependence. This is reminiscent of our MR terms. We will control for these trade-diverting factors of other flows by including spatially weighted average neighborhood GDP at both the origin and destination. The weighting matrices based on both k4 and inverse distance are tested. We reintroduce traditional activity variable Y for completeness. The resulting model in equation (6) below is an SLX variety of baseline and has the benefit of estimator flexibility, compared to other spatial econometric models.

$$X_{ij,t} = exp\ [\beta_0 + \beta_1 lnDIST_{ij} + \beta_2 (lnDIST_{ij} x lnDIESEL_{ij,t}) + \beta_3 NEIGHBOR_{ij} + \beta_4 HOME_{ij} + \beta_5 REGION_{ij} + \beta_6 lnY_{i,t} + \gamma_1 W_o lnY_{i,t} + \beta_7 lnY_{j,t} + \gamma_2 W_d lnY_{j,t} + \eta_{i,t} + \theta_{j,t}] + \epsilon_{ij,t} \quad \epsilon \sim (0, \sigma_\epsilon^2) \qquad (6)$$

We run both the PPML and OLS model specifications for the spatial model for comparison. The PPML model is included for direct comparison to our baseline results and properly account for heteroskedasticity and zero trade. The OLS model requires a natural log transformation of the dependent variable plus a constant of 1 to include the zero trade observations. A dummy equal to 1 for zero trade observations is included to improve the fit. The estimated parameters γ_1 and γ_2 are considered local spillovers, but are mainly intended to be control variables. Similar to fixed effects, they may very well be insignificant. Kelejian et al. (2011) include similar variables, using a weighting scheme analogous to our inverse distance matrix. They describe the origin lag, in our case $\mathbf{W}_{\mathrm{o}} lnY$, as market potential of other trade partners (sellers) on the supply side. Similarly, the destination lag, $\mathbf{W}_{\mathrm{d}} lnY$, is market potential of demand (other buyers). While our autocorrelation of trade volume was shown to be positive in Section 4.2, when we apply our inverse distance weight matrix to GDP we are introducing competition and expect the coefficient to be negative (or insignificant). That is, controlling for bilateral size, a larger relative neighborhood should divert and lower trade flows. In the case of k4 weights where the GDP of only 4 nearest states are averaged, the neighborhood is small and not discounted by distance, thus the expectations are not so clear. For example, k4 weighted variable may capture agglomeration effects: if immediate neighbors of a state are larger/active, then more trade may be attracted to the state's multistate region in the first place. If so, the effect on the coefficient would be in opposite direction of competition effects.

Table 6 reports the results of both the conventional model and the SLX model using the PPML specification in Columns 1-3 and the OLS specification in Columns 4-6. The standard errors are clustered at the Origin-Destination pair.[1] First, we notice that the PPML estimators of interest, i.e., the coefficients for both *lnDIST*×*lnDIESEL* and *lnDIST,* are comparable to the baseline results in Table 4. Second, we confirm the findings of Silva and Tenreyro (2006) that OLS estimation results offer biased estimates, specifically for lnDist. The F-test of the null hypothesis that the estimates are equal in the two models results in a χ^2 value of 5.84 with 1 degree of freedom and a p-value of 0.0156. This demonstrates that linear spatial econometric models are not comparable with our conventional specification.

Looking closer at the estimates for the spatial lag terms, the point estimates for the coefficients for spillover variables with k4 weights are positive but insignificantly different from zero, which confirms our concerns over using a small neighborhood. When the inverse distance matrix is used, the point estimates for both coefficients are negative and similar, but only the destination spillovers are significant. Kelejian et al. (2011) find similar results even when they include a spatial error (SER) component. The spatial model results show that even when incorporating spatial interdependence directly into the estimation, our results are virtually unchanged, especially our coefficient of interest. Next, we will move forward with our baseline model and utilize its structure to incorporate interdependence in a counterfactual exercise.

6. Counterfactual

[1] We also examine alternative clustering schemes. When the standard errors are clustered by Origin, the origin lag of GDP is significant (p=.000) and destination lag of GDP is barely significant (p=.049). When the standard errors are clustered by Destination, origin lag of GDP is insignificant (p=.204) and destination lag of GDP is significant (p=.000) Ultimately, these are control variables so robustness in terms of significance is not priority.

Given the oil price and the distance relationship found in the baseline model, we will consider the effects of a national 10% price shock on trade patterns in the last period using a counterfactual experiment. Conceptually, the rising cost of transportation will be passed on to consumers of transportation services, such as trucking, through surcharges to save profit margins. In an Armington world, consumers will need to reallocate their bundle of goods, given their budget constraint, to account for higher transportation costs. To get close to their previous utility, consumers are expected to purchase goods closer to them, where the transportation costs are not as high. However, goods from different origins are imperfect substitutes. The changes to the reallocation of trade patterns will then result in welfare loss. We will use general equilibrium to quantify such social welfare effects.

6.1 General Equilibrium Trade Impact Framework

Using baseline model parameters to predict changes in trade flows yields only a partial trade impact (PTI) and does not consider the interdependence of trade flows, multilateral effects, or feedback from changes in size. Since multilateral resistance contains our observable trade costs, any shock to the cost variables will change each state's multilateral resistance and subsequently the trade flows. Accounting for this factor results in a modular trade impact in which the trade flow distribution occurs in a different "module" than the determinants of output and expenditure (Anderson, 2011; Head and Mayer, 2014). Taking this framework one step further by including adjustment in expenditures and output, we capture the general equilibrium trade impact (GETI).

$$GETI_{ij} = \frac{X'_{ij}}{X_{ij}} = \underbrace{exp\left[\beta\left(t'_{ij} - t_{ij}\right)\right]}_{\text{PTI}} \times \frac{\Pi_i \mathrm{P}_j}{\Pi'_i \mathrm{P}'_j} \times \frac{Y'_i Y'_j}{Y_i Y_j} \quad (7)$$

GETI will be a ratio of trade *X* between counterfactual scenario and baseline, easily convertible to percentage change. Fally (2015) shows that structural gravity estimation with PPML yields fixed effects estimates completely consistent with multilateral resistance equations (2) and (3) and are recovered as following:

$$(\Pi_i)^{1-\sigma} = Y_{j0} Y_i \exp(-\hat{\eta}_i) \tag{8}$$

$$(\mathrm{P}_j)^{1-\sigma} = \frac{Y_i}{Y_{j0}} \exp(-\hat{\theta}_j) \tag{9}$$

The vector X is used to construct output $Y_i = \sum_j X_{ij}$ and expenditure $Y_j = \sum_i X_{ij}$. Y_{j0} is the expenditure of a reference importer. Finally, η and θ are estimated coefficients on origin and destination fixed effects, respectively. In a panel setting, multilateral resistance will vary by year and requires one reference importer for each year.

Next, we follow Anderson, Yotov, and Larch (2015), and estimate the general equilibrium through three general steps utilizing the properties of PPML and structural form of gravity. First, our baseline model is estimated with a further reduced form of (5) where there is no intercept and GDP terms are dropped. One importer fixed effect is dropped for each year and corresponds to reference importer. It has no consequence on the final GETI results. The estimation equation is the following:

$$X_{ij,t} = exp\,[\beta_1 lnDIST_{ij} + \beta_2(lnDIST_{ij} x lnDIESEL_{ij,t}) + \beta_3 NEIGHBOR_{ij} + \beta_4 HOME_{ij} + \beta_5 REGION_{ij} + \eta_{i,t} + \theta_{j,t}] + \epsilon_{ij,t} \quad \forall i,j,t \quad \epsilon \sim (0, \sigma_\epsilon^2) \tag{10}$$

Then, the predicted values of X are computed to use as the baseline data to avoid capturing the model error as part of the trade impacts. At this point we can retrieve the baseline MR terms using (8) and (9) above. Second, we define our counterfactual trade cost, a nationwide 10% increase in diesel prices in the last time period of our sample. Next, equation (10) is estimated again on the original data X, while constraining all bilateral trade cost coefficients. This will estimate a new set of coefficients for the fixed effects, and the MR terms can be computed again. Third, we allow for endogenous adjustments to values of output and expenditure in an endowment economy. This happens through changes in factory gate prices in (11) caused by changes in the previous step.

$$p_j = \frac{Y_j^{\frac{1}{1-\sigma}}}{\gamma_j \Pi_j} \tag{11}$$

The price p_j is the supply price and γ_j is a distribution parameter of the CES utility function. Once a new set of output, expenditure and subsequent changes in trade data X are found, the second step is repeated to find new MR terms. Again, step 3 needs to be repeated to retrieve new output and expenditure. Multiple feedbacks take place until the market clears and the price does not change. Finally, the welfare effect, which is the loss of income or real GDP, is defined below in (12) and is consistent with that presented by Arkolakis et al. (2012).

$$\widehat{W} = \frac{Y_i'/\widehat{\mathrm{P}}_i'}{Y_i/\widehat{\mathrm{P}}_i} \tag{12}$$

6.2 GETI Results

The general equilibrium results of the 10% price shock show a more realistic picture of the trade impact, including non-obvious distributional effects, compared to the partial trade impact. We pick one state, Massachusetts, as the origin and consider all other states as destinations to showcase our results in Figure 4. Massachusetts trades less will all other states, losing more trade with remote partners. For example, trade to New York falls by 0.47 percent and falls by 2.91 percent to California, a 2.43 percentage point difference. Interestingly, Massachusetts increases trade within its own border by 0.53 percent. Anderson and van Wincoop (2003) have emphasized that trade effects in general equilibrium tend to be smaller overall, which holds true in our case. In the unreported PTI results, trade from Massachusetts falls 3.4 percent to New York and falls 5.7 percent to California. Furthermore, since GETI considers multilateral and feedback effects, the same shock results are more heterogeneous (Figure 4) compared to the PTI (Figure A1). For example, we do not see a uniform "wave" pattern anymore and states such as Illinois and Georgia lose more trade from Massachusetts than expected, compared to states of similar distance. This is because a state is able to adjust imports and exports in response to changes in multilateral cost, which changes both their own and other states' output and expenditure, and then feeds back into adjusting trade volumes. These effects can only be discovered in general equilibrium, as heterogeneity arises from the composition of each state's trade partners and interdependence through substitution.

In the general equilibrium, the pattern of diesel price effects on trade across space is still present despite heterogeneity and feedback effects. Anderson (2011) discusses the offsetting feedback of multilateral resistance in the theoretical structural gravity model, where it is expected that the same percentage shock to trade costs across all partners will result in no net change of trade volumes. However, our results show that trade volumes have a net change, at both the flow and state levels. Figure 5 plots the percentage changes in trade for each individual trade flow across distance. The overall trend of trade falls more across distance. Some trade volumes increase at smaller distances, which can be attributed to the substitution of trade with local options. Most often this occurs by states trading more within their own borders, as seen in

Table A1 of Appendix, where every state, besides California and Texas, has increased home trade. Having aggregated trade flows to the state level, we see a net decrease for imports and exports across all states. When we aggregate to inter-regional flows (their percentage changes are shown in Table A2 of the Appendix), we see a clear effect present along the diagonal indicating smaller trade loss with a region compared to out of region. Contrast to the GETI results in Figure 5, the percentage changes in trade across distance are all negative and have a smaller variance in the PTI framework (Figure A2 of the Appendix), indicating more homogeneous effects of an oil price shock without considering the dynamics leading to the general equilibrium.

Given the net effects of a state's trade flows on output and expenditure, we compute the welfare effects in terms of income or real GDP. We find that each state suffers a welfare loss from the price shock, with the median being a 0.69% income loss. The welfare effects are not uniform, ranging from 0.55% in states like Connecticut to 0.97% in Alaska. Finally, we convert the percentage change in income for every state into 2012 dollars and aggregate to find a national effect of $82 billion in lost income. While this is only a small fraction of the U.S. real GDP, it is noticeable considering the annual GDP growth rates and given such a modest price shock.

7. Conclusion

In this paper we apply a structural gravity model to trade flows within the United States and explore the heterogeneous trade effects of oil price shocks. In a setting of inter-state and inter-regional trade, we see that overall the effects of diesel price increases with magnitude across distance and distance creates more friction at higher prices. Our results are robust, notably across multiple robustness subsamples and through a spatial econometric specification used to account directly for spatial interdependence present among trade flows. In a general equilibrium where we account for multilateral and feedback effects, the pattern remains, and a higher price makes trade relatively more local and leads to a negative net social welfare effect for the nation. We also find heterogeneous trade effects on different states and regions resulting from a uniform price shock. This result surpasses the theoretical expectations of gravity trade models discussed by Anderson (2011). These consequences need to be considered in the design of spatially blind national oil tax policy and state fuel taxes. Furthermore, obvious policy implications include technological progress towards alternate energy sources in transportation to curb reliance on oil and sensitivity to fluctuations. Interestingly, Combes and Lafourcade (2005) conclude that transportation technology was a more important factor than energy for transport costs. Our findings should motivate further studies overlapping energy and trade, since energy dependence continues to pose a challenge.

It is worthwhile to note that calculating GETI in an aggregate trade flow model only accounts for heterogeneity resulting from each state's trading partner composition and multilateral costs. Since the oil price effect is across distance, states are affected differently depending on distance to all of their own trading partners as well as each of their partners' composition of partners and costs. We recognize that our model does not account for some sources of heterogeneity in the price-distance interaction effect across trade flows. It may be the case that certain trade pairs are more or less responsive to price shocks due to factors such as industry links and commodity composition. (Lankhuizen et al, 2015, Yilmazkuday, 2012). Another dimension is that of transportation mode accessibility. Indeed, price effects may differ by mode and substitutability across modes would matter. The implication is that areas or trade corridors that rely heavily on a specific mode will be affected by shocks differently, and areas with flexible modes may not have to substitute between partners to such a degree. An analysis of mode-specific trade data will provide additional insight. Future research efforts will also link interstate trade with international trade to increase the domain of distance and potentially strengthen its effect and magnify the heterogeneity present in the system. Local and regional trade may prove to be relatively even more important because of existing trade agreements for instance.

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Table 1 Descriptive Statistics

	Flows ≥0					Flows>0				
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Xij (Trade $m)	7803	4720.69	30157.91	0	1432562	6645	5543.35	32610.69	1	1432562
lnDist	7803	6.82	0.9	1.3	8.57	6645	6.72	0.88	1.3	8.57
lnRDiesel	7803	1.03	0.36	0.49	1.44	6645	1.04	0.36	0.49	1.44
lnYi	7803	12.08	1.03	10.11	14.59	6645	12.18	1.03	10.11	14.59
lnYj	7803	12.08	1.03	10.11	14.59	6645	12.18	1.02	10.11	14.59
Home	7803	0.02	0.14	0	1	6645	0.02	0.15	0	1
Region	7803	0.12	0.32	0	1	6645	0.13	0.34	0	1
Neighbor	7803	0.08	0.28	0	1	6645	0.1	0.3	0	1

Table 2 Percentage of Region Outflows

	Origin							
Destination	Far West	Lakes	Mideast	NewEng	Plains	Mountain	Southeast	Southwest
Far West	**70.46**	3.61	4.34	4.11	5.90	14.19	3.54	4.15
Lakes	4.58	**58.50**	8.86	5.01	14.01	5.70	9.18	3.34
Mideast	4.50	8.15	**61.76**	16.49	4.65	4.20	7.26	2.47
NewEng	1.19	1.53	5.69	**62.02**	1.05	0.92	1.18	0.53
Plains	1.92	7.29	2.23	1.54	**53.29**	6.13	2.67	2.84
Mountain	4.25	1.50	0.82	0.56	2.25	**53.52**	0.79	1.44
Southeast	6.20	13.84	12.66	7.07	10.78	6.99	**68.28**	8.15
Southwest	6.90	5.57	3.64	3.19	8.07	8.35	7.11	**77.07**
Total	100	100	100	100	100	100	100	100

Table 3 Moran's I of Trade Flow Xij

Weight	2002	2007	2012
Population Share	.0633 (.001)	.0463 (.001)	.0331 (.001)
Destination: k4	.0807 (.001)	.0636 (.002)	.0511 (.005)
Origin: k4	.0826 (.003)	.0561 (.007)	.0442 (.007)
Destination: Distance	.0369 (.001)	.0303 (.003)	.0225 (.004)
Origin: Distance	.0394 (.001)	.0284 (.001)	.0214 (.005)

P-values with 999 permutations in parenthesis

Table 4 Baseline Results

VARIABLES	(1) PPML X>0	(2) PPML X≠S	(3) PPML $X \geq 0$	(4) PPML X>0	(5) PPML X≠S	(6) PPML X≥0
lnDiesel×lnDist	-0.085***	-0.085***	-0.078***	-0.085***	-0.085***	-0.078***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
lnDist	-0.558***	-0.559***	-0.608***	-0.558***	-0.559***	-0.608***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
lnYi	0.567***	0.614***	0.848***			
	(0.05)	(0.06)	(0.04)			
lnYj	1.577***	1.564***	0.795***			
	(0.12)	(0.12)	(0.06)			
Home	1.638***	1.634***	1.540***	1.638***	1.634***	1.540***
	(0.14)	(0.14)	(0.15)	(0.14)	(0.14)	(0.15)
Region	0.305***	0.305***	0.306***	0.305***	0.305***	0.306***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Neighbor	0.599***	0.597***	0.573***	0.599***	0.597***	0.573***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Constant	-16.057***	-16.404***	-8.235***	9.936***	7.091***	9.279***
	(1.75)	(1.80)	(1.42)	(0.56)	(0.51)	(1.17)
Observations	6,645	6,696	7,803	6,645	6,696	7,803
FEit	YES	YES	YES	YES	YES	YES
Fejt	YES	YES	YES	YES	YES	YES
LL	-2.355e+06	-2.360e+06	-2.827e+06	-2.355e+06	-2.360e+06	-2.827e+06

Robust standard errors (clustered by State pair)
in parentheses *** p<0.001, ** p<0.01, * p<0.05

Table 5 Robustness- Truck Sample

VARIABLES	(1) PPML X>0	(2) PPML X≠S	(3) PPML X≥0
lnRDiesel*x*lnDist	-0.101***	-0.101***	-0.088***
	(0.02)	(0.02)	(0.02)
lnDist	-0.618***	-0.641***	-0.703***
	(0.03)	(0.03)	(0.04)
Home	1.718***	1.664***	1.568***
	(0.08)	(0.08)	(0.09)
Region	0.357***	0.357***	0.365***
	(0.03)	(0.03)	(0.03)
Neighbor	0.681***	0.662***	0.641***
	(0.04)	(0.04)	(0.04)
Constant	9.764***	10.862***	9.388***
	(0.18)	(0.37)	(1.12)
Observations	5,938	6,470	7,803
FEit	YES	YES	YES
FEjt	YES	YES	YES
LL	-1.783e+06	-1.839e+06	-2.269e+06

Robust standard errors (clustered by State pair) in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 6 Spatial Model Results

VARIABLES	(1) PPML X	(2) PPML X	(3) PPML X	(4) OLS Ln(X+1)	(5) OLS Ln(X+1)	(6) OLS Ln(X+1)
lnDieselxlnDist	-0.078***	-0.078***	-0.078***	-0.076**	-0.076**	-0.076**
	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
lnDist	-0.608***	-0.608***	-0.608***	-0.744***	-0.744***	-0.744***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
	(0.04)	(0.09)	(0.09)	(0.03)	(0.04)	(0.05)
(Wo)lnYi	-	0.040	-0.685	-	0.085	-0.279
	-	(0.18)	(0.47)	-	(0.05)	(0.21)
lnYj	0.795***	0.600***	0.860***	0.909***	0.812***	0.920***
	(0.06)	(0.07)	(0.05)	(0.06)	(0.04)	(0.04)
(Wd)lnYj	-	0.063	-0.735**	-	-0.001	-0.908***
	-	(0.14)	(0.27)	-	(0.08)	(0.18)
Home	1.540***	1.540***	1.540***	2.002***	2.002***	2.002***
	(0.15)	(0.15)	(0.15)	(0.17)	(0.17)	(0.17)
Region	0.306***	0.306***	0.306***	0.414***	0.414***	0.414***
	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
Neighbor	0.573***	0.573***	0.573***	0.762***	0.762***	0.762***
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)
zero	-	-	-	-4.433***	-4.433***	-4.433***
	-	-	-	(0.07)	(0.07)	(0.07)
Constant	-8.235***	-5.899	7.998	-11.090***	-9.833***	1.751
	(1.42)	(3.85)	(9.80)	(0.74)	(1.22)	(3.90)
Weights	-	K4	DIST	-	K4	DIST
R-squared	0.991	0.991	0.991	0.932	0.932	0.932
Observations	7,803	7,803	7,803	7,803	7,803	7,803
FEit	YES	YES	YES	YES	YES	YES
FEjt	YES	YES	YES	YES	YES	YES
LL	-2.827e+06	-2.827e+06	-2.827e+06	-9173	-9173	-9173

Robust standard errors (clustered by origin-destination pair) in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Figure 1 Diesel Prices

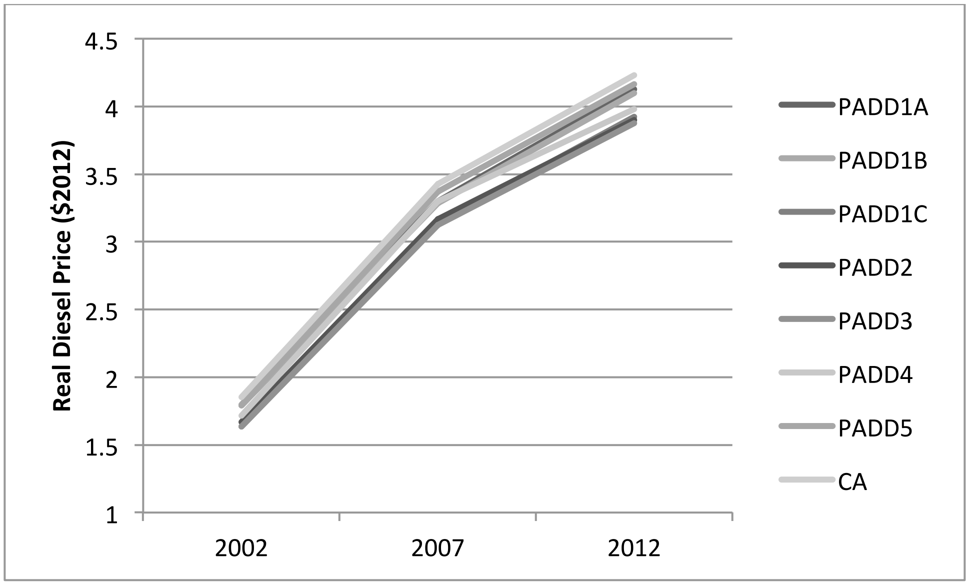


Figure 2 Export Composition

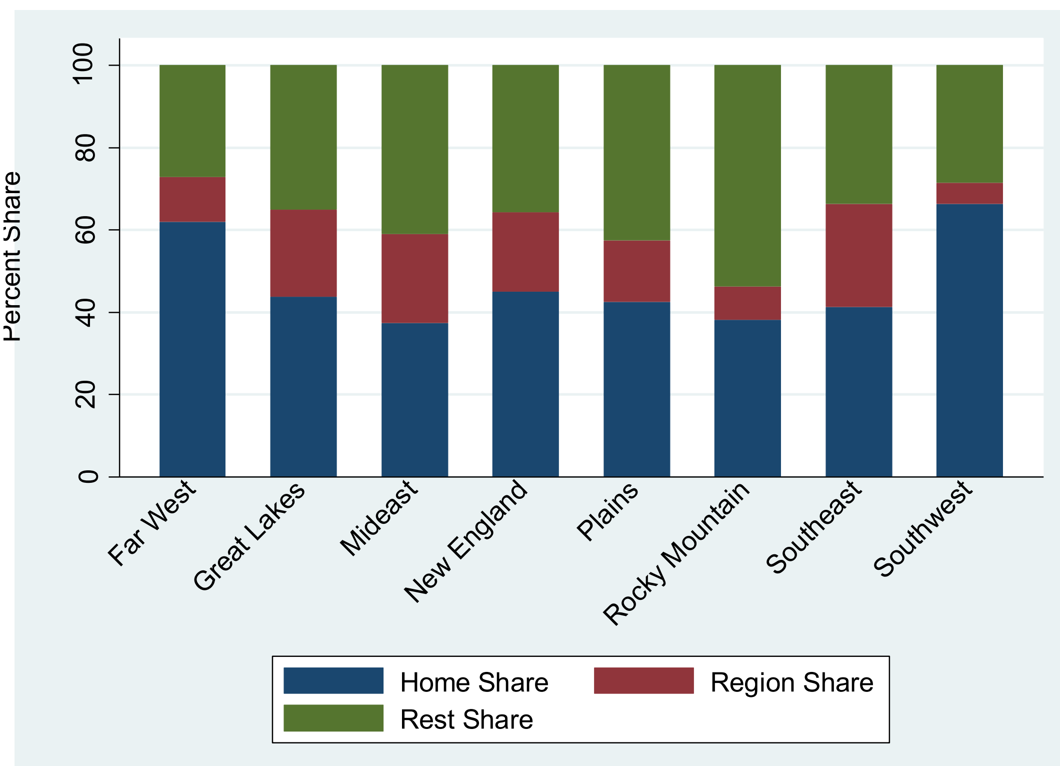


Figure 3 Distance Elasticity and Price Elasticity

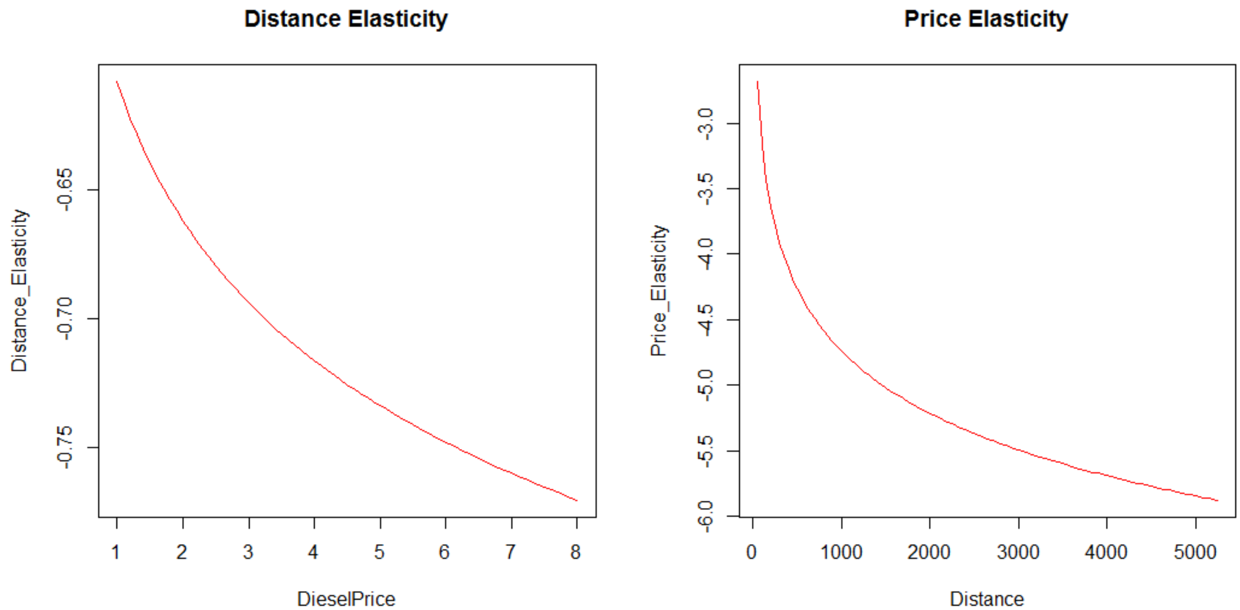


Figure 4 GETI 10% Price Increase (Massachusetts Origin)

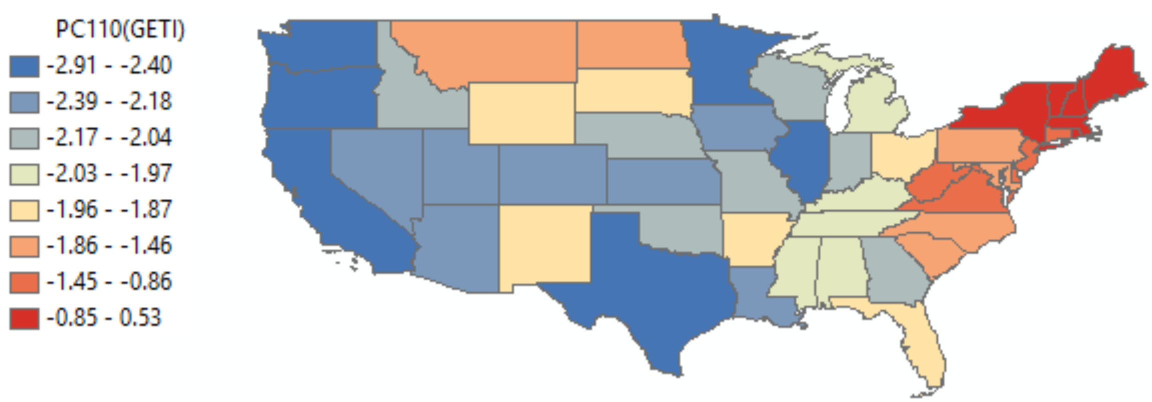
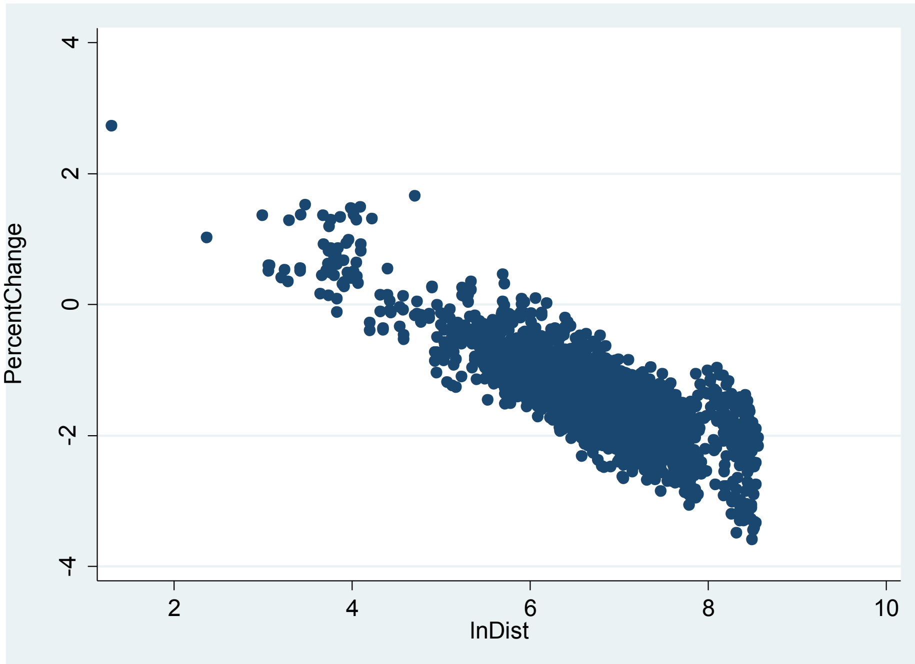


Figure 5 Percentage Changes of Trade Flow From a 10% Increase in Price



Appendix:

Table A1 State Level GETI Indices (Percentage Change)

State	Trade Home	Exports Regional	Imports Regional	Exports Else	Imports Else	Exports Total	Imports Total	Welfare Total
AL	0.67	-0.67	-0.74	-1.57	-1.55	-1.08	-1.13	-0.69
AK	1.66	-1.06	-1.56	-2.15	-1.59	-2.13	-1.59	-0.97
AZ	0.82	-1.33	-1.35	-1.62	-1.25	-1.56	-1.26	-0.69
AR	0.99	-0.76	-0.76	-1.15	-1.08	-1.00	-0.96	-0.76
CA	-0.17	-1.10	-1.61	-1.77	-2.16	-1.66	-2.08	-0.65
CO	0.76	-0.49	-0.69	-1.47	-1.45	-1.36	-1.38	-0.70
CT	0.41	-0.59	-0.71	-1.04	-1.23	-0.97	-1.15	-0.55
DE	1.36	-0.34	-0.27	-1.27	-1.28	-0.84	-0.81	-0.69
DC	2.73	-0.53	-0.15	-1.33	-0.96	-1.04	-0.68	-0.70
FL	0.32	-1.83	-1.12	-2.39	-1.68	-2.16	-1.45	-0.64
GA	0.44	-0.87	-0.90	-1.78	-1.75	-1.28	-1.30	-0.64
HI	1.37	-1.56	-1.06	-2.95	-1.89	-2.92	-1.88	-0.74
ID	1.37	-0.18	-0.34	-1.33	-1.17	-1.13	-1.06	-0.83
IL	0.14	-0.96	-1.15	-1.35	-1.76	-1.24	-1.56	-0.58
IN	0.45	-0.89	-0.82	-1.34	-1.57	-1.16	-1.22	-0.62
IA	0.72	-0.66	-0.71	-1.32	-1.41	-1.16	-1.23	-0.69
KS	0.64	-0.68	-0.69	-1.25	-1.44	-1.14	-1.27	-0.71
KY	0.62	-0.72	-0.88	-1.25	-1.31	-1.04	-1.15	-0.66
LA	0.52	-1.17	-0.99	-1.71	-1.51	-1.52	-1.33	-0.64
ME	1.36	-0.28	-0.25	-1.46	-1.24	-1.22	-1.05	-0.78
MD	0.60	-1.10	-0.78	-1.07	-1.02	-1.08	-0.95	-0.57
MA	0.53	-0.65	-0.61	-1.51	-1.50	-1.35	-1.31	-0.58
MI	0.34	-0.88	-0.76	-1.61	-1.79	-1.33	-1.31	-0.64
MN	0.51	-0.74	-0.99	-1.54	-1.82	-1.37	-1.63	-0.65
MS	0.86	-0.62	-0.58	-1.51	-1.38	-1.04	-0.97	-0.72
MO	0.62	-0.86	-0.77	-1.27	-1.25	-1.20	-1.16	-0.67
MT	1.31	-0.43	-0.06	-1.55	-1.01	-1.41	-0.90	-0.84
NE	0.94	-0.51	-0.51	-1.28	-1.45	-1.07	-1.16	-0.75
NV	1.29	-0.93	-0.62	-1.43	-1.41	-1.23	-1.05	-0.78
NH	1.29	-0.19	-0.15	-1.47	-1.28	-1.13	-0.99	-0.72
NJ	0.35	-0.66	-1.02	-1.59	-1.87	-1.18	-1.54	-0.56
NM	1.48	-0.66	-0.62	-1.29	-0.98	-1.02	-0.85	-0.84
NY	0.17	-1.28	-0.87	-1.36	-1.12	-1.34	-1.05	-0.56
NC	0.43	-0.74	-0.98	-1.48	-1.62	-1.12	-1.32	-0.67
ND	1.30	-0.63	-0.35	-1.33	-1.29	-1.17	-1.00	-0.82
OH	0.28	-1.03	-0.99	-1.38	-1.58	-1.28	-1.37	-0.63

OK	0.86	-0.79	-0.91	-1.38	-1.19	-1.15	-1.10	-0.70
OR	0.86	-1.10	-1.14	-1.82	-1.84	-1.51	-1.53	-0.71
PA	0.30	-0.92	-0.98	-1.44	-1.47	-1.27	-1.33	-0.63
RI	1.02	-0.40	-0.35	-0.89	-1.05	-0.76	-0.84	-0.55
SC	0.72	-0.66	-0.59	-1.61	-1.57	-1.11	-1.05	-0.69
SD	1.34	-0.39	-0.27	-1.23	-1.31	-0.99	-0.98	-0.81
TN	0.50	-0.68	-0.79	-1.39	-1.47	-1.03	-1.13	-0.68
TX	-0.13	-0.99	-0.92	-1.88	-1.63	-1.75	-1.56	-0.62
UT	0.92	-0.59	-0.51	-1.61	-1.42	-1.46	-1.30	-0.70
VT	1.52	0.04	-0.09	-1.17	-1.10	-0.88	-0.87	-0.78
VA	0.48	-1.32	-1.01	-1.06	-1.00	-1.15	-1.00	-0.64
WA	0.40	-1.68	-1.11	-2.30	-1.86	-2.14	-1.64	-0.65
WV	1.19	-0.69	-0.70	-1.01	-0.95	-0.89	-0.86	-0.76
WI	0.49	-0.66	-0.74	-1.42	-1.67	-1.12	-1.25	-0.67
WY	1.49	0.00	-0.13	-1.22	-1.06	-0.94	-0.89	-0.86

Table A2 Region Trade Flow GETI (Percent Change)

	Origin							
Destination	Far West	Lakes	Mideast	New Eng	Plains	Mountain	Southeast	Southwest
Far West	**-0.16**	-2.12	-2.53	-2.58	-1.73	-1.20	-2.23	-1.84
Lakes	-2.37	**-0.09**	-1.62	-1.93	-1.26	-1.95	-1.49	-2.16
Mideast	-2.49	-1.41	**-0.05**	-0.39	-1.79	-2.17	-1.22	-2.36
New Eng	-2.38	-1.53	-0.55	**0.28**	-1.74	-2.08	-1.62	-2.31
Plains	-1.82	-1.08	-1.93	-2.05	**0.22**	-1.14	-1.46	-1.48
Mountain	-0.97	-1.42	-1.92	-1.99	-0.80	**0.61**	-1.60	-1.25
Southeast	-2.08	-1.24	-1.18	-1.71	-1.31	-1.75	**-0.10**	-1.59
Southwest	-1.41	-1.63	-2.13	-2.24	-1.11	-1.14	-1.48	**-0.13**

Figure A1 PTI 10% Price Increase (Massachusetts Origin)

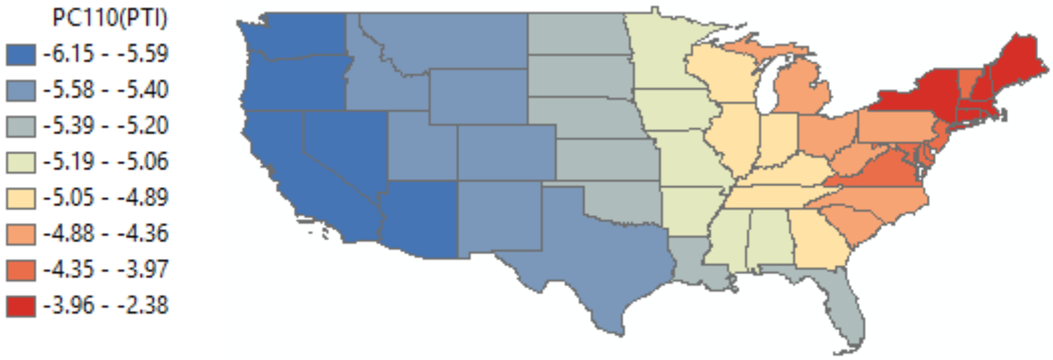


Figure A2 PTI Percentage Changes of Trade Flow From a 10% Increase in Price